NOVEL DISTRIBUTED WAVELET TRANSFORMS AND ROUTING ALGORITHMS FOR EFFICIENT DATA GATHERING IN SENSOR WEBS

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ABSTRACT

In this work we present our ongoing investigation of novel approaches for information processing and representation in a sensor web. Since sensor nodes capture spatially and temporally correlated information there are several alternatives in order to exploit correlation, namely, (a) sensors can exploit this spatial correlation by first exchanging data and then compressing it in a distributed manner, or (b) sensors can exploit temporal correlation locally only, or (c) sensors can even exploit correlation across time and space. We aim to develop techniques based on the last approach, which will tend to reduce the total amount of data to be transferred in the sensor web at the expense of some additional (potentially minor) power consumption. We are investigating methods for sampling, routing, processing and compression. All of these aim at maximizing the quality of the data available at the fusion center for a given energy consumption target at the nodes. Two types of methods for exploiting spatio-temporal correlation between sensors are presented here. First we consider a compression scheme based on a distributed 2D wavelet transform along arbitrary routing trees and discuss its extension to include a temporal component of the transform. Second, we explore techniques that involve "sub-sampling", i.e., where data is not captured by all nodes, (including methods based on traditional sampling, as well as new approaches based on compressed sensing). Investigation of joint routing and compression optimization is also underway for both classes of methods, with preliminary results presented here. The techniques presented here provide a variety of ways to exploit data correlation through the routing choices made, the compression choices made across time and space, and the joint decisions on compression and routing, ultimately leading to lower cost and higher quality data. We also discuss the current status of an implementation of the distributed wavelet transform on a practical sensor platform, as well as extensions of our algorithms to take advantage of radio range characteristics of these sensors.

1. INTRODUCTION

Wireless sensor networks (WSN) can offer mobility and versatility for a variety of applications, such as object detection/tracking, environment monitoring and traffic control [1]. Still, one of the main obstacles they face is that they often rely on batteries for power supply; thus limiting their energy consumption becomes essential to ensure network survivability.

When from multiple correlated sources is acquired, aggregation involving in-network data compression can offer a more efficient representation of measurements, significantly reducing the amount of information that needs to be transmitted over the network, thus leading to a potentially large reduction in energy consumption. Prior work has addressed a number of distributed source coding (DSC) methods as a means to decorrelate data. While some rely on information exchange and additional computation inside the network to propose distributed versions of transforms, such as Karhunen-Loève [2] and wavelets [3], others propose schemes that do not require internode communication, such as networked Slepian-Wolf coding [4, 5]. In general, DSC techniques face a trade-off between i) more processing at each node to achieve more compression and ii) less processing which would require more information (bits) to be sent to the sink. This trade-off has also been addressed by previous research. Pattem *et al* [6] provide an analysis on the regions in a network that should favor compression over routing based on the impact of spatial correlation of the measurements. The performance of aggregation under a more general data model is considered by Goel and Estrin [7].

Our focus has been on the problems of (i) finding an optimal assignment of compression algorithms to nodes that minimizes total energy consumption and (ii) finding data aggregation structures that best exploit spatial data correlation across nodes in terms of a cost-distortion trade-off. We primarily investigate two basic trade-offs associated with problems (i) and (ii). The *first basic trade-off* comes in the selection of number of levels of decomposition for a wavelet transform, although the same principle can be extended to other classes of signal representation and compression. We seek to achieve efficient signal compression by exploiting spatial signal correlation (e.g., temperature measurements in neighboring nodes in a sensor network will tend to be similar). In general, coding schemes that remove correlation across multiple nodes will tend to lead to higher coding efficiency, but at the cost of increased "local" communications, i.e., a distributed approach means that nodes have to exchange data before the final compressed version (which is sent to the fusion node) can be generated.

The *second trade-off* is that between aggregation trees that result in energy-efficient routing, i.e. shortest path routing trees (SPT), and ones that allow a transform to de-correlate data effectively. Since data is compressed as it is routed to the sink along some given routing tree, correlation is only exploited along those pre-defined paths. Considering an SPT, it guarantees that the path from a given node to the sink is most efficient for routing, but obviously does not guarantee that consecutive nodes in a path contain highly correlated data. Thus, correlation may not be exploited effectively along an SPT and can result in less efficient coding.

In our earlier work based on path-wise wavelet transforms and recent work extending these ideas to 2D wavelet transforms, we focused on methods that exploit data correlation by applying a

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spatial transform to snapshots of data from every node in the network. However, it may also be possible to collect only a subset of measurements in a structured manner and still achieve high quality data reconstruction. For example, in compressed sensing [8–10], if a signal is known to be "sparse" in a particular basis (i.e., it can be represented by a small number of coefficients in some know basis) then only a small subset of measurements is needed to reconstruct the entire set of data. As such, we also consider methods that only capture measurements from a subset of nodes as an alternative to transforms that sample data from every node in the network.

This paper describes our recent progress in the development of novel distributed compression algorithms for sensor webs, under funding from the NASA-ESTO AIST program. We begin with a summary of results pertaining to compression algorithms in Section 2, including our proposed entropy coding method, 2D wavelet transforms, space-time transforms, and a variety of sub-sampling methods that provide an alternative to our wavelet transforms. Networking related issues are also discussed in Section 3. We have already started implementing various aspects of the system using programmable sensors with an eye towards testing our system both in-lab and within a small scale real-life deployment (Section 4). To conclude, we summarize the project status briefly in Section 5.

2. COMPRESSION COMPONENTS

This section summarizes the compression tools we have developed. A synopsis of our proposed entropy coding technique is provided in Section 2.1. We also provide a detailed summary of our recently proposed 2D wavelet transforms (Section 2.2) along with preliminary extensions of our transforms to exploit correlation across both time and space (Section 2.3). As an alternative to our proposed transforms, a randomized subsampling method based on compressed sensing is discussed (Section 2.4) along with a set of techniques based on traditional subsampling methods (Section 2.5).

2.1. Entropy Coding

Our previous work did not explicitly consider variable length encoding of the outputs of the distributed wavelet transform. In [11], we addressed the task of using entropy coding to minimize the communication cost between sensor nodes. To simplify our analysis, we assume unidirectional transmission in a sequence of equally spaced nodes with no path merges. For our variable length codes we use the family of Golomb codes [12, 13]. Golomb codes are known to be optimal for geometric distributions of nonnegative integers [14]. An important step in coding is to determine the value of the code parameter m to minimize the average code length for a given distribution. We adopt the sequential parameter estimation method used in LOCO-I [15] image compression. In this method the parameter m is chosen to be the smallest power of 2 that is greater than the average absolute value of past observed sequence. In our framework, these values are readily available as we decode the history information from past nodes. Simulation results using our proposed method are presented in Section 2.3.

2.2. 2D Wavelet Transforms

In our recent work [16] a 2D wavelet transform was developed along an arbitrary routing tree using wavelet lifting. It exploits 2D correlation across paths unlike the path-wise transforms proposed in [17–20] while remaining computable in a unidirectional manner unlike previously proposed 2D wavelet transforms [21, 22], thus avoiding additional overhead due to backward data transmissions.

To implement a lifting transform [23] two things must be defined at each level of decomposition: (i) a method for splitting data points into even and odd sets and (ii) a method for computing predict and update operators. In our proposed transform, we split according to a splitting tree at each level, where nodes of odd (even) depth in the tree are odd (even) in the transform. Predict and update filters are linear and employ simple averaging and smoothing as detailed in [16]. A unidirectional computation algorithm is also provided as well as a 2D transform optimization method using dynamic programming. A sample network is shown in Figure 1, where splitting trees for 2-levels are shown along with an example of unidirectional computation.

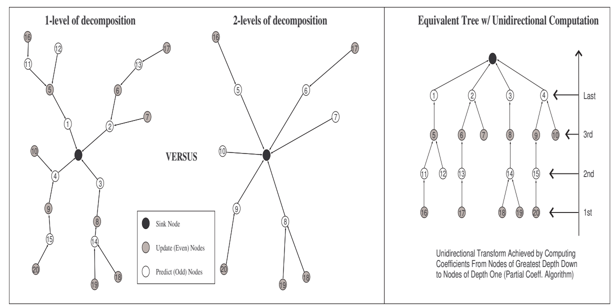


Fig. 1. Trees used for splitting. Black node is the sink

Performance curves are shown in Figure 2, showing the tradeoff between total energy consumption and reconstruction quality. A comparison is made against the path-wise transform in [20] and the 2D transform in [21]. Our method clearly outperforms both, mainly since it exploits our *first basic trade-off* by exploiting data correlation across adjacent routing paths and by choosing among a number of different levels of decomposition via our optimization method.

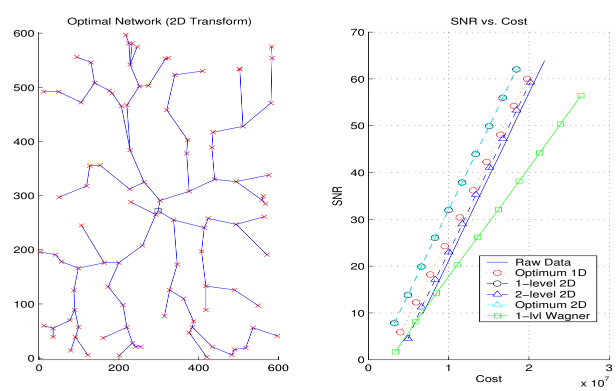


Fig. 2. Energy consumption comparison shown on the right. Optimal levels of decomposition for a uniform network shown on the left. Red x's denote 1-level nodes and green circles denote 2-level nodes.

2.3. Space Time Transforms

We focus on monitoring applications of sensor networks, in which all nodes continuously collect data to monitor environmental conditions such as temperature, humidity, seismic activity, etc. Due to the nature of the physical phenomenon being monitored, the sensing data collected by the network often exhibits high time correlations (intra-node) as well as high spatial correlation (inter-node). These spatial and temporal correlations brings significant advantages for the development of joint space-time compression technologies.

Most existing sensor-web data compression work has been focused on inter-node correlations, i.e., considered spatial compression only. However, there are some notable exceptions, e.g., [24] [25] [26] [27], which considered various approaches for data reduction through temporal processing. In [26] and [27], temporal data reduction was achieved by *suppression*, i.e., a node only transmits data when an interesting event (e.g., big change in data value) has been detected. The major challenge to this approach is how to choose the a priori threshold for change detection. The lightweight temporal coding (LTC) method [24] attempts to represent the time series data with a single linear model and send only the parameter of this model. However, for data that can not be modeled as linear sequences, the LTC method is not likely to work. The distributed predictive coding (DPC) method [25] extended distributed source coding (DSC) [4] [28] to scenarios where each source has memory, and exploited temporal correlation by linear predictive coding. The major challenge for distributed predictive coding is due to the conflicts that arise between distributed coding and prediction. In other words, optimal distributed quantization may compromise the prediction effectiveness at each source encoder. An iterative encoder-decoder design was proposed in [25] in order to cope with this problem. However, this method might be impractical for sensor web applications due to its complexity.

In this work, we focus on data aggregation-based compression methods for sensor networks, where data are transmitted through multiple hops along a pre-defined routing path, and compressed jointly as they hop around the network. Figure 3 illustrates an example of the information flow along a 1D routing path in such systems. Each vertex in the graph represents a certain point in the space-time domain, i.e., can be identified by its node and time indexes. The solid edges in the graph represent real data transmissions between nodes; and the dashed edges represent the availability of historical information, both spatially and temporally, that can be exploited to encode data of a node at any given time. For example, to encode data of node $n+1$ at time $t+2$ (highlighted as red in the graph), we can use all the information from current node $n+1$ and its parent node n at all time instances T satisfying $T \leq t+2$ (shown as shaded in the figure).

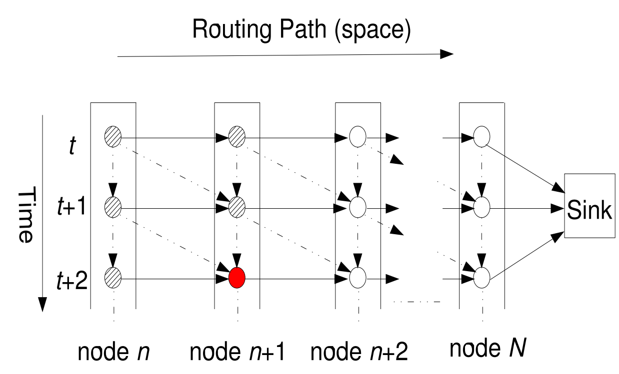


Fig. 3. Information flow along a 1D path in an aggregation-based data transmission system.

This might look like a conventional 2D sequential image compression problem. However, there are some fundamental differences that arise due to the constraints in a sensor network. First of all, there exists an asymmetry in the system, i.e., temporal processing is local and much cheaper than spatial processing therefore should be fully exploited to minimize the transmission cost; second, backwards communication is usually prohibited and therefore the nodes in the beginning of the routing path always have very limited spatial historical information to explore; furthermore, there is usually a delay constraint which needs to be considered when designing the temporal processing techniques. For example, if a transform is used for temporal decorrelation, the filter length and the level of decomposition may have to be delimited depending on the desired delay constraints.

As an initial step of evaluating potential benefits of using spatial-temporal encoding for sensor network, we performed some preliminary experiments using a wavelet transform based method. In this approach we applied a single stage DWT on the data sequence at each node to exploit temporal redundancy, and performed spatial compression using distributed wavelet transform and entropy coding technique as presented in our previous work [11]. In figure 4 we show the rate distortion performance of various approaches: a) combined spatial-temporal coding using 2D separable wavelet transforms, b) spatial compression only using the technique as described in [11], and c) baseline approach of entropy coding quantized sample differences. In this example we use 10-bit source data generated as quantized version of 2D second-order Auto Regressive process with poles at $0.99e^{\pm j\pi/64}$. The gap between the curves represents benefits of combined spatial-temporal compression compared to spatial only compression alternatives.

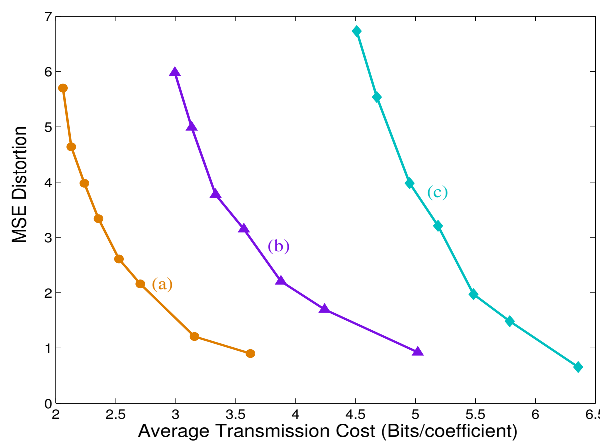


Fig. 4. This rate-distortion graph shows the benefit of (a) Combined spatial-temporal coding and (b) Spatial compression only, compared to the baseline approach of (c) entropy coding quantized sample differences (spatial only).

There are many potential avenues for further exploration of joint spatial-temporal compression. For wavelet-based techniques, we may: a) explore additional level of temporal decompositions; b) perform adaptive bit allocation across nodes taking into account their temporal behavior. An alternative to transform-based approach is to use adaptive filtering [29] [30]. In adaptive filtering, each sample value is predicted from the historical data and the difference between the estimate and actual value is encoded and transmitted. The estimation error is also used to update the filter weights. We are currently investigating this technique.

2.4. Compressed Sensing

In this work, we are investigating applications of compressed sensing (CS) with multi-hop routing. CS is a promising method that can reconstruct a K-sparse signal, x, of dimension N from only M measurements of the signal [8] [9]. The measurements, $y \in R^M$, are obtained via a linear matrix-vector multiplication $y = \Phi x$, with $K \ll M \ll N$. The measurement matrix (Φ) which represents how the measurements are formed from samples is an $M \times N$ matrix whose elements could be chosen to be random coefficients, e.g., discrete values generated with a Bernoulli distribution or continuous values generated by a Gaussian distribution.

To apply CS to wireless sensor networks, we consider energy cost and routing which prior CS work has not taken into account. In most previous work, each measurement is obtained as linear combinations of all input samples, i.e., Φ is a full matrix. This approach cannot be directly applied to wireless sensor networks due to high energy consumption it requires. Based on the assumption that energy is dissipated only during data transmission among sensors, we need to design an algorithm that efficiently collects M measurements then transmits them to the sink. The focus is on designing measurement matrices that are both incoherent with the sparsity inducing basis (as required to ensure reconstruction from a small number of measurements) and also lead to efficient routing.

In general, with increasing number of measurements, lower coherence and higher reconstruction quality are obtained. However, with a given number of measurements, the correlation between coherence and reconstruction quality is low. For this reason, the idea of investigating row-by-row partial coherence minimization algorithm for obtaining the measurement matrix did not yield expected results; i.e. the measurement matrix generated by the algorithm shows a bit lower or almost same performance with down-sampling (DS) in terms of reconstruction quality and energy cost.

Our results to date show that a naive randomized spatial downsampling is efficient (on average) both in terms of reconstruction quality and energy cost for AR data as well as data synthesized to be compressible in DCT and multi-level Haar bases. Figure 5 shows that DS consumes less energy for the same level of reconstruction quality than dense random projection (DRP) and sparse random projection (SRP) [10]. The reasons for such performance are that, for the DCT basis, the measurement matrix with downsampling is highly incoherent and for the Haar basis, the trend of coherence vs. number of measurements is very similar for the different choices of measurement matrix.

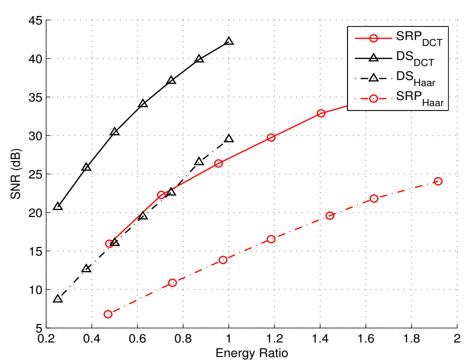


Fig. 5. Energy ratio vs. SNR of DS and SRP projections for AR data. DRP is out of range due to very high energy cost.

Figure 6 shows the relative performance of CS-based and 2D wavelet based [16] algorithms. For the low SNR region, CS with DS projection can provide a higher SNR at the same cost. With the 2D wavelet scheme as the bit budget is increased the accuracy in reconstructing wavelet coefficients increases so that SNR performance improves. However, in the case of compressed sensing the achievable SNR for compressible data is limited (unless the number of projections increases significantly.)

Random choice of sensors for downsampling with CS is attractive since it allows completely distributed and load-balanced operation. Also, it is not restricted to bandlimited signals (as long as they are sparse or compressible). We are now investigating alternative scenarios in which aggregation holds promise by exploiting local sparseness. As a further extension, our initial study was restricted to a grid topology and we are now working on extending this to more general topologies.

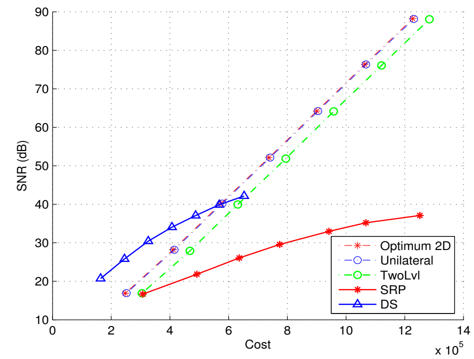


Fig. 6. CS with DCT basis vs. 2D wavelet transform. For the low energy cost region, CS with DS projection can provide higher SNR. As the energy budget grows, 2D wavelet transform gets better.

2.5. Subsampling Methods

This work considers how a sleep schedule for nodes can be seen as a spatio-temporal transform of the data. Realistic data from a sensor field has temporal evolution as well as spatial propagation, and often those spatial and temporal characteristics are nonseparable, e.g., temporal evolution can be different at spatially close nodes.

Consider data distributed along 1-dimensional routing path, where at each node some temporal sub-sampling pattern has been used. Thus, we can also view this as a 2-dimensional dataset, where sleep scheduling of nodes along this path as induced a 2-D sampling. In the Figure 7 the two axes represent spatial and temporal direction, respectively, and red dots indicate data sensing at each node at each time. If we calculate the transmission cost of the sensed data to the sink, total energy consumption is proportional to the number of sensed data points. If we undersample the data along either direction we can reduce the number of sensed data points, but the gathered data may be undersampled so that there will be error in reconstruction. To improve data quality for a given number of sensed data points, we suggest checkerboard shaped sampling pattern. This kind of pattern places the replicated frequency spectrum of the data farther apart than the spatial-only or temporal-only undersampled cases. With low-pass filtering in the frequency domain and inverse Fourier transform, the data can be reconstructed with less degradation due to aliasing.

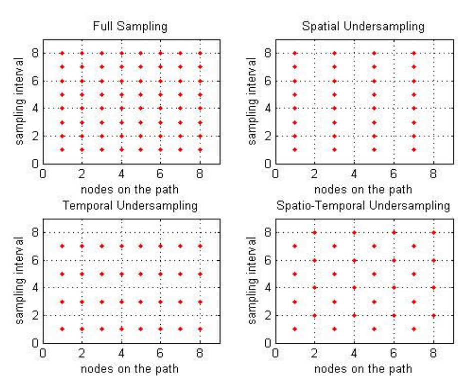


Fig. 7. Various Sampling Patterns for Spatio-Temporal Data.

Figure 8 compares the reconstruction quality and total energy consumption for the proposed method and the temporal-only case with various undersampling factors, for the dataset in [31]. The result shows that we can attain up to 2.6 dB gain with the same amount of energy consumed for data transport.

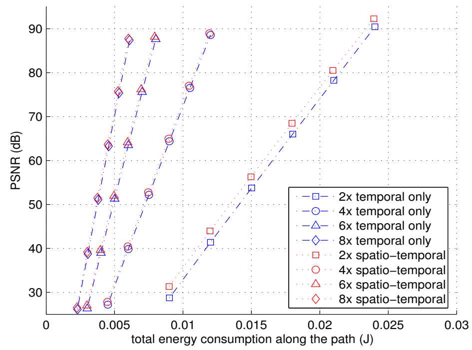


Fig. 8. Reconstruction Quality vs. Total Energy Consumption

2.6. Spatio-temporal filtering

As mentioned in Section 2.5, general data from the sensor field is nonseparable spatio-temporal data. If some data have characteristics that data evolution along time accompanies spatial propagation, it may be more efficient to find cross-correlation between data points from different nodes at different time stamps. In other words, at time t_k and t_{k+1}, cross-correlation can be better between data points at different nodes i and j, than data points at the same node i. Thus, it can be beneficial to find the spatio-temporal data sequence which has the best cross-correlation in the data space and filter the data along that direction, instead of filtering the data temporally and spatially, respectively. We are currently investigating practical techniques to exploit this intuition.

3. NETWORKING COMPONENTS

In this section, we investigate a variety of networking issues including joint transform and routing optimization (Section 3.1) and the design of erasure-correcting codes to ensure reliable delivery in our system (Section 3.3). We also explore the potential performance improvements when the broadcast capability of wireless sensors is exploited (Section 3.2).

3.1. Joint 2D Transform and Routing Optimization

We consider the 2D transform detailed in Section 2.2, which can be computed along an arbitrary routing tree. As mentioned before, performing a transform along an efficient routing tree (i.e., SPT) may not be efficient from a joint routing and compression standpoint. Since data correlation between nodes is typically inversely proportional to the distance between them, and since an SPT does not guarantee short distances over each hop (only short overall distance), an SPT will not guarantee high data correlation over each hop. Thus, some coding efficiency will be lost when encoding data along an SPT. On the other hand, we can consider a Minimum Spanning Tree (MST) constructed from a graph with edge weights defined by inter-node correlation. Such an MST guarantees that each node shares a link with its highest correlation neighbor and will therefore be more efficient from a coding standpoint. However, it will not guarantee efficient routing of data to the sink since some links may force nodes to forward data away from the sink. As an alternative to either efficient routing trees (SPT) or efficient coding trees (MST), our recent work [32] developed methods that search for combinations of these two trees that achieve a good trade-off between coding efficiency and routing cost. In particular, we exploit our *second basic trade-off* by finding the minimum cost combination of the two trees under distortion constraints.

An example of such trees for a 40 node network is shown in Figure 9 with corresponding performance curves in Figure 10. We search for an optimal combination of an SPT (with distance based edge weights) and MST (with correlation based edge weights). The "Optimal Tree" in Figure 9 shows the minimum cost combination of SPT and MST found by exhaustive search and the "Heuristic Tree" shows the combination found by our proposed heuristic, the details of which can be found in our paper. A gain of 2.5 to 3 dB is attained by using our proposed joint optimization algorithms over our transform along an SPT, as shown in Figure 10.

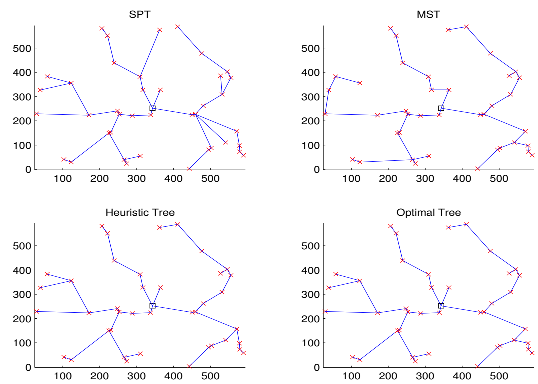


Fig. 9. SPT, Heuristic, and Minimum Cost Trees.

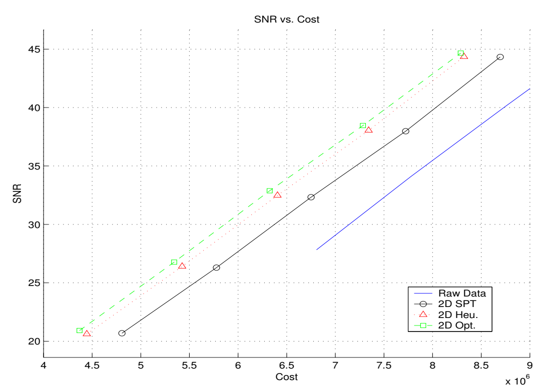


Fig. 10. Performance Comparisons Different Trees.

3.2. Exploiting Broadcast Capability

Our current 2D lifting transforms [16] work over trees and ignore the broadcast nature of wireless transmissions. We observe that data flow along the tree is required primarily for invertibility of the transform. Overheard broadcasts can potentially be used to increase the compression rates by further taking advantage of local correlations. The idea is to design invertible transforms that allow nodes to use data from their descendants in the aggregation/routing trees and additionally, others that are within communication range.

Suppose we are given a static tree T, in which links are relatively stable. The broadcasts of even (update) nodes at depth $d+1, d+2, \ldots, \max$ depth might reach multiple odd (predict) nodes at depth $1, 2, \ldots, d$, all of which can use this data for improved predictions i.e., greater decorrelation. This is particularly useful when an odd node hears such broadcasts from even nodes that are not its children in T.

For given graph $G(V, E)$ and tree graph $T(V, R)$ ($R \subset E$), we can exploit these broadcasts by using the following algorithm:

- Split vertices of G into even and odd groups based on depth in T
- Build a graph T_A by augmenting T with links in $E \backslash R$ from even nodes at any depth d to odd nodes at any depth $1, 2, \ldots, d-1$. This is illustrated in Figure 11.
- Use T_A for predict computations at odd nodes and T for update computations at even nodes

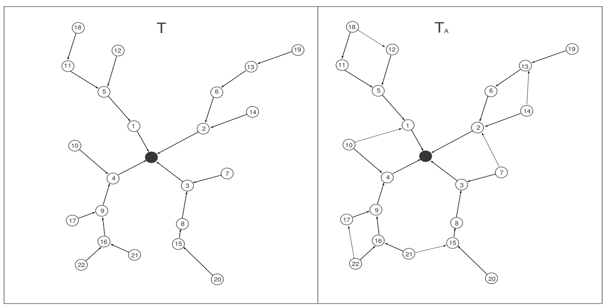


Fig. 11. Example of Tree with Broadcast Graph.

Constructing the transform in this way still preserves invertibility. Furthermore, this can still be computed in a unidirectional manner simply by adding a term to the partial coefficient equations corresponding to the broadcast neighbors. However, many open questions still remain pertaining to the best choice of nodes to use broadcast, filter coefficient design, etc. This topic is still under investigation.

3.3. Erasure-Correcting Codes

A major challenge in networking the low-power low-capability radios of the sensor nodes is that many communication links will be highly unreliable and lossy, showing asymmetry and large temporal fluctuations, due to multipath fading effects and individual hardware variance. We have investigated several approaches in [11] to improve the reliability of network communications, including routing algorithms, network coding, and channel coding on individual links. Our work to date has included an investigation of rateless erasure-correcting codes suitable for application to node-to-node links subject to large fluctuations in link availability. Based on our investigation to date we plan to use off the shelf erasure correcting codes, rather than devote additional efforts to studying novel techniques.

4. IMPLEMENTATION

We have implemented the unidirectional, invertible 2D wavelet scheme in NesC/TinyOS. Tmote Sky devices, which have an Atmega processors and CC2420 radios, were used for the experiments. The implementation is completely distributed and flexible - it can work for any given tree. However, local tree information such as the parent, child and grandchild ids are assumed to be available at each node. For efficient operation in a real network, packetization is an additional requirement. Multiple measurements and coefficients need to be stored at nodes until they can fill a packet. Full coefficients are uniformly quantized and stuffed into packets based on the bit allocation. There is added overhead since maximum and minimum over the stuffed values are also included in the packet for reconstruction. The packets are forwarded along the tree to a base station (laptop), where the inverse operations are performed. Reconstruction code is in MATLAB.

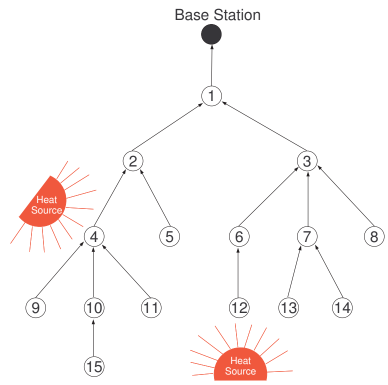


Fig. 12. Experiment setting and routing tree

A network of 15 Tmote sky nodes is used for an evaluation. The sensed phenomena is ambient temperature, in which gradients are introduced by switching hot lamps on and off. The same sequence and timing of switches is repeated with different average bit allocation. In each experiment, all nodes have the same bit allocation. The experiment setting and routing is illustrated in Figure 12.

bits per sample	normalized cost	average MSE
2	.79	.036
4	.85	.00057

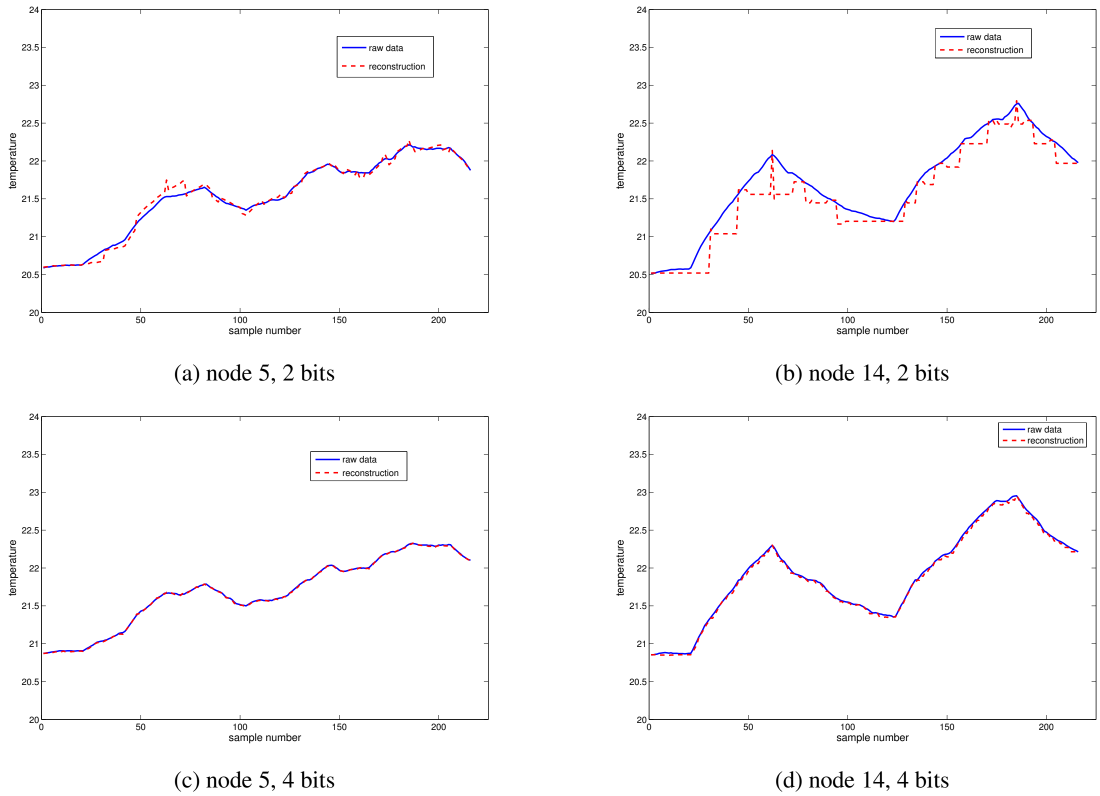
Fig. 13. MSE versus Cost comparison for 2 and 4 bits allocated per sample

The raw data samples are 16 bits each. As seen in Figure 14, with 2 bits allocated per sample, the reconstruction is able to capture the trend. With 4 bits allocated, the reconstruction is very close to the measured signal. The performance in terms of average mean-squared error vs the cost for the different bit allocations is shown in the table in Figure 13. The cost is the total number of packets required in the experiments and is normalized by the cost for sending raw data measurements over the same routing tree. These results illustrate the tradeoff between cost and reconstruction quality, along with verifying the correctness of the implementation.

We are currently working on introducing robustness mechanisms to handle packet losses. A further goal is to develop a modular architecture for distributed compression in sensor networks. The current implementation provides insights into some of the modules that might be part of such an architecture.

4.1. Collaboration plans

We are pursuing several avenues to define specific science environments for which to customize our techniques and on which to deploy simple test systems, if possible. In considering what is feasible we are taking into consideration the capabilities of the motes (our target sensor development and testing platform.) We are in particular focusing on what can be done given the measurement sensor types, communication ranges, etc. The JPL investigators have started to develop a plan to select specific NASA applications that could be suitable to demonstrate our techniques. Further, we



(a) node 5, 2 bits (b) node 14, 2 bits

(c) node 5, 4 bits (d) node 14, 4 bits

Fig. 14. Reconstruction performance examples for different bit allocations

have identified a target environment for demonstrating the effectiveness of our compression techniques. AIMS (Australian Institute of Marine Sciences) is deploying WSNs to monitor growth, development and health of the corals at the Great Barrier Reef. Our aim is to set up a long-standing (greater than 1 month) medium size (50-100 motes) WSN test bed in conjunction with AIMS. The plan is to implement and test joint routing and compression algorithms for data collection from the test bed, in addition to non-trivial tree construction and sleep scheduling algorithms developed by ANRG.

5. CONCLUSIONS

In this paper we have provided an overview of a collaborative project that is designing new approaches for gathering, compression and representation of spatially correlated data in a sensor network. This project spans a range of issues, from signal representation and compression optimized for 2D irregularly sampled measurements, to the design of efficient erasure codes to ensure reliable operation. We are working on a testbed system to validate our designs.

6. REFERENCES

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